Hybrid scheme for modeling local field potentials from point-neuron networks

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While recordings of extracellular potentials in neural tissue are commonly used for monitoring neural activity, interpretation of the low frequency part, the local field potential (LFP), remains ambiguous in terms of the underlying network activity. Studies have shown that the LFP depends on electrode position, extracellular volume conductor model, neuronal morphology, synapse distributions and synaptic input correlations [1,2,3]. In order to relate spiking dynamics in point-neuron neuron network models to extracellular signals, e.g., the LFP, we have developed a hybrid scheme that uses the spiking activity (Fig. panel A) generated by a network of single-compartment leaky integrate-and-fire model neurons (implemented in NEST [4]). The network provides synaptic input to populations of detailed multi-compartmental neuron models (Fig. panel B) which are used to compute the spatiotemporal LFP pattern (Fig. panel C) based on biophysical principles behind extracellular electric signals using LFPy (http://compneuro.umb.no/LFPy) [5] and NEURON [6]. The hybrid scheme is incorporated in a new, publicly available Python package named hybridLFPy (http://github.com/espenhgn/hybridLFPy).

We here demonstrate an application of the method with the network model of [7] describing the local microcircuitry under 1 mm^2 surface of cat primary visual cortex. The point-neuron network includes ~77000 cells in total distributed across four layers, each composed of one excitatory and one inhibitory population representing layers 2/3 through 6, activated by external input (cortico-cortical, thalamo-cortical). For the LFP model, the same amount of neurons, subdivided into 16 cell types with passive membrane properties are used with cell-type and layer-specific connectivity derived from the point-neuron network description and additional anatomical data [8]. Our results show that both spontaneous and stimulus-evoked LFPs depend critically on the level of synchrony in the underlying network state. Besides, we show that full-scale simulations, i.e., simulations including all cells in the network, are required to address the effect of network correlations on the LFP. Furthermore, the hybrid scheme can be used to develop and verify simplified models for LFP generation from point-neuron network models. Given the widespread use of point-neuron network models and the previous lack of tractable methods to associate their activity to easy-to-measure signals (e.g., LFPs), the present method is a step toward gaining important insight into the link between experimental measurements and the underlying network activity.

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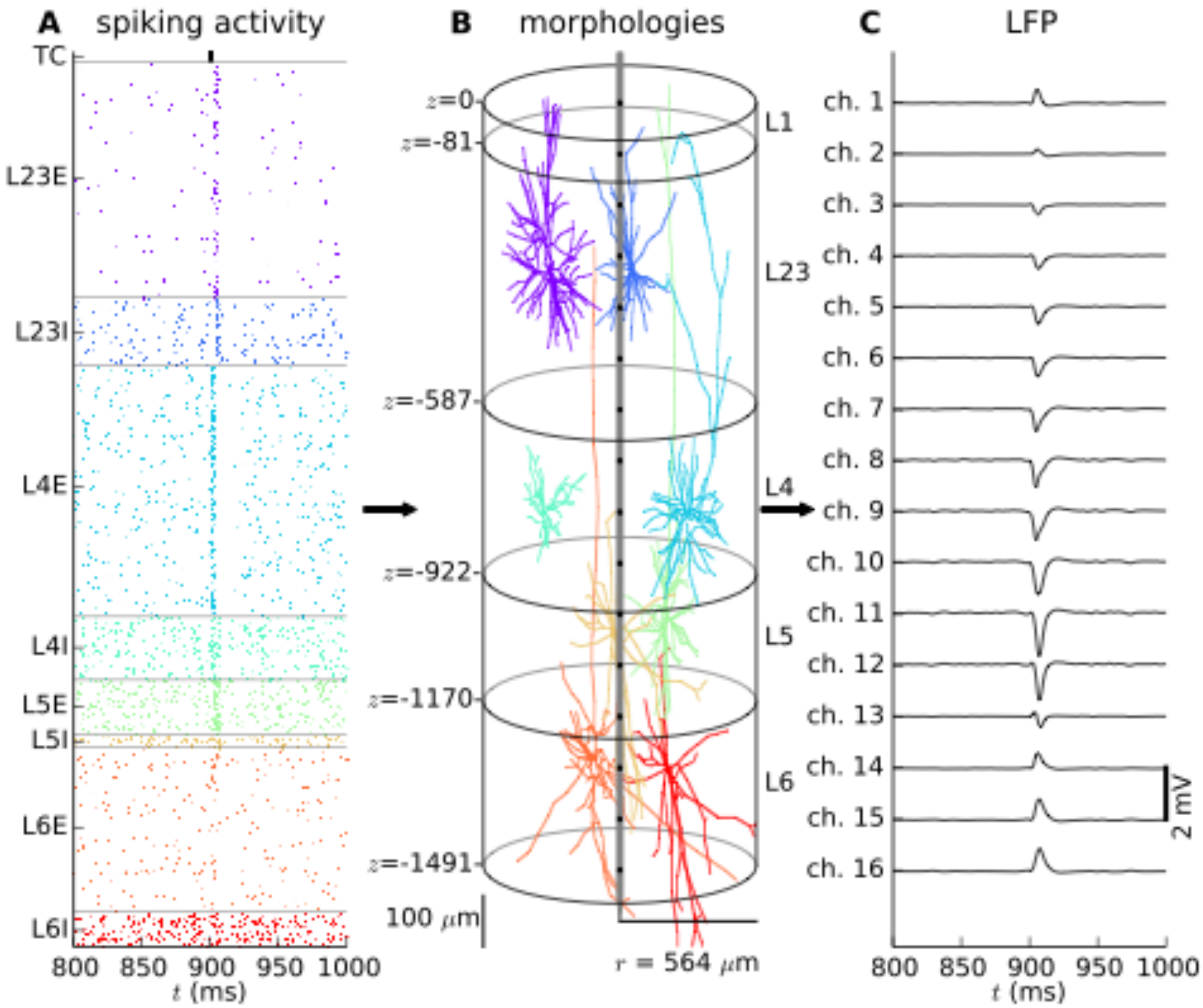

A spiking activity
TC
L23E
L23I
L4E
L4I
L5E
L5I
L6E
L6I
800 850 900 950 1000
t (ms)
B morphologies
z=0
z=-81
z=-587
z=-922
z=-1170
z=-1491
L1
L23
L4
L5
L6
100 μm
r = 564 μm
C LFP
ch. 1
ch. 2
ch. 3
ch. 4
ch. 5
ch. 6
ch. 7
ch. 8
ch. 9
ch. 10
ch. 11
ch. 12
ch. 13
ch. 14
ch. 15
ch. 16
2 mV
800 850 900 950 1000
t (ms)